METHOD OF ESTIMATING A SIGNAL-TO-
INTERFERENCE+NOISE RATIO (SINR)

5   **BACKGROUND OF THE INVENTION**

1. Field of the Invention

The present invention relates to wireless communication, and more particularly, a
method of estimating a signal-to-interference+noise ratio.

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2. Description of Related Art

Signal-to-Interference+Noise Ratio (SINR) is an important metric of
communication link quality. SINR estimation is of particular importance for wireless
data systems where resources are shared dynamically amongst users. Some applications
15 of SINR estimates are: a) Power Control in CDMA Systems: the receiver estimates the
SINR, compares it to a target and commands the transmitter to increase/decrease its
transmitted power; and b) Rate Adaptation: the information bit-rate assigned to a user
can be dynamically varied based on its link quality and the system load. While such
adaptation has limited use in voice systems, it is extremely useful for wireless data
20 systems. Consequently, inaccurate SINR estimates can severely degrade performance
and resource utilization.

                    SUMMARY OF THE INVENTION

In the method of estimating a signal-to-interference+noise ratio (SINR) according
25 to the present invention, a conventionally known SINR estimate is scaled and translated
to produce a SINR estimate that has a substantially reduced mean square error. The
SINR estimator according to the present invention operates on either pilot symbol
samples or data symbol samples. Further according to the present invention, a pilot
symbol based SINR estimate and a data symbol based SINR estimate are weighted and

combined to generate a composite SINR estimate having a reduced mean square error as compared to either of the individual estimators.

BRIEF DESCRIPTION OF THE DRAWINGS

5   The present invention will become more fully understood from the detailed description given herein below and the accompanying drawings, which are given by way of illustration only, and thus are not limitative of the present invention, and wherein:

Figure 1 illustrates pilot and data symbols multiplexed in a time slot;

10   Figure 2 illustrates the gain from the SINR estimator according to an embodiment of the present invention as compared to a conventional estimate based on pilot symbols only for different smoothing factors.

Figure 3 illustrates optimal weights assigned to a pilot-symbol based estimator and a data-symbol based estimator in a combined estimators; and

15   Figure 4 illustrates the performance of the combined estimator using the estimated weights.

DETAILED DESCRIPTION OF THE PREFERRED EMBODIMENTS

20   In describing the method of estimating the signal-to-inteference+noise ratio according to the present invention, only Binary Phase Shift Keying (BPSK) modulation is considered although the methods and related analysis can be extended to other signaling schemes. Noise and interference are modeled together as additive white Gaussian noise (AWGN), but as will be appreciated from the following disclosure, this

25   should not limit the application of the method according to the present invention. Transmission is organized into fixed duration timeslots, each containing pilot and data symbols as shown in Fig. 1. The channel attenuation and phase shift, assumed fixed over a timeslot, are treated as unknown constants rather than as random variables (no fading assumption).

30   First, to better understand the method according to the present invention, the conventional SINR estimation will be described. Typically, the received signal

corresponding to the jth transmitted symbol (pilot or data) in the kth time slot is defined as

$$(1)$$

$$Y_{kj} = a_{kj}\mu_k + \varepsilon_{kj} \quad j = 1, 2, ..., N,$$

5

where μ_k represents the received signal amplitude (product of transmitted amplitude and channel gain), ε_{k_j} is a random variable that represents the noise+interference, a_{k_j} represents the symbol-value, and N is the number of samples (pilot or data). Information symbols could be +1 or –1 (in BPSK), while it is assumed (without any loss of

10   generality) that pilot symbols are always +1. It is also assumed that the distribution that characterizes the noise+interference is Gaussian with zero mean and variance σ^2. The SINR in the kth time slot is defined as:

$$(2)$$

$$\Theta_k = \frac{\mu_k^2}{\sigma^2}$$

15   and is the parameter to be estimated.

The groups of N sample points (data or pilot) could correspond to a time slot in CDMA systems or frames in TDMA systems. A well-known pilot-symbol sample based estimator of SINR is computed as the ratio of the square of the sample mean of the received to the pilot-symbol sample Y (based on N sample points in a group) to the

20   corresponding sample variance is a reasonable estimator of the SINR. Estimators based on this ratio are called Squared Mean By Variance or SMV estimators. Different SMV estimators have been studied in the literature and they only differ in the normalization constant used to compute the sample variance.

For the case where the $\{Y_{kj}\}$ values correspond to pilot symbols, define the

25   sample mean and unbiased sample variance for the kth time slot as

$$(3)$$

$$\overline{Y}_k = \frac{1}{N} \sum_{j=1}^{N} Y_{kj}$$

$$(4)$$

$$S_k^2 = \frac{1}{N-1} \sum_{j=1}^{N} (Y_{kj} - \overline{Y}_k)^2 \cdot$$

Then, $\hat{\Theta}_k = \left(\overline{Y}_k\right)^2 / S_k^2$ is one possible SMV estimator (commonly used). The Maximum

Likelihood (ML) estimator of the SINR is also an SMV estimator where a biased sample

variance estimate is used in the ratio (normalization is by N rather than N-1). The signal

power, μ_k^2, varies due to channel fading. However, the noise variance, σ^2, changes very

5   slowly with time, typically with the addition (departure) of a call; therefore, one can

improve the overall quality of the SINR estimate by using a longer-term moving average

estimate of the sample variance. This makes the "effective" number of samples used in

the sample variance estimate larger and therefore more accurate. One simple method to

accomplish this is through exponential smoothing of a set of sample variance estimates

10   (called Exponentially Weighted Moving Average or EWMA). The smoothed sample

variance estimate through the kth time slot would be given by:

(5)

$$\hat{\sigma}_k^2 = (1-r)\hat{\sigma}_{k-1}^2 + rS_k^2 \quad k \geq 1,$$

where r is the smoothing factor determined according to desired design parameters

15   and $0 < r \leq 1$. The SINR estimate at the end of k time slots then becomes:

(6)

$$\hat{\Theta}_k = \frac{\left(\overline{Y}_k\right)^2}{\hat{\sigma}_k^2}.$$

The accuracy (mean and variance) of SMV estimators based on using a single group of

20   pilots with N sample points is known in the art. However, aside from simulation results,

the accuracy of SMV estimators that utilize EWMA for sample variance estimation is not

known.

     The inventors have analytically analyzed the accuracy of SMV estimators that

utilize EWMA for the sample variance estimate and have developed accurate

25   approximations for the bias, variance and MSE of such estimators. From this analysis,

the inventors developed a characterization of the bias and variance, and hence the MSE,

of such estimators. The inventors, based on their analysis, developed a scaling and

translation methodology for the SINR estimators that substantially reduces the MSE. The

scaled and translated EWMA SINR estimator according to the present invention is:

(7)

$$\tilde{\Theta}_k = \frac{\eta - 2}{\eta} \hat{\Theta}_k - \frac{1}{N},$$

where $\left(-\frac{1}{N}\right)$ is the translation and η is the scaling factor defined as:

(8)

$$\eta = \frac{(N-1)(2-r)}{r}.$$

Note that this scaling factor η depends only on parameters that are fixed and known at the receiver and do not require any separate estimation procedure.

The gains due to scaling and translation (measured as the reduction in mean-squared error) in using $\tilde{\Theta}_k$ instead of $\hat{\Theta}_k$ can be substantial especially for larger values of the smoothing factor r as seen in Figure 2. Figure 2 illustrates the gain (measured as the reduction in MSE) based on pilot symbols only for different smoothing factors r, and show that even for values of r around 0.5-0.6, the gain is around 30-40%.

SMV estimators that use data symbols are also known in the art. A commonly used SMV estimator based on data symbols, called the non-coherent estimator, is one where the sequence $\{Y_{kj}\}$ is replaced by the sequence of its absolute values i.e. $\{Z_{kj}=|Y_{kj}|\}$. The SINR estimate for the kth time slot is the ratio of the sample mean and sample variance of the sequence $\{Z_{kj}\}$. Smoothing of the sample variance of the $\{Z_{kj}\}$ sequence via the EWMA approach may also be used to improve accuracy. While the scaling and translation approach developed in this invention can be extended to any SMV estimator based on data symbols, including the non-coherent estimator, the preferred approach is outlined in concurrently filed Application No. _____ entitled "Method of Estimating a Signal-to-Interference+Noise Estimate Using Data Samples" by the inventors of the subject application.

The accuracy of the SINR estimate can be further enhanced by simultaneously utilizing estimates from pilot symbols as well as data symbols in the estimation process. As mentioned before pilot symbols have the advantage of being known at the receiver

but are relatively fewer in number. Data symbols are more plentiful than pilot symbols but they are unknown at the receiver.

First, a method for the general problem of optimally linearly combining two estimates of an unknown parameter will be described. With that foundation, the combining method will be applied to SINR estimation with pilot and data symbols.

Suppose there are two noisy estimates, $\hat{\Theta}_1$ and $\hat{\Theta}_2$, respectively, of a parameter Θ. Furthermore let the biases of the two estimates be $B_1 = E[\hat{\Theta}_1] - \Theta$ and $B_2 = E[\hat{\Theta}_2] - \Theta$, respectively, and the variances be τ_1^2 and τ_2^2, respectively. The MSE of $\hat{\Theta}_i$ is $MSE_i = B_i^2 + \tau_i^2$, $i = 1,2$. Consider the class of estimators formed by an arbitrary linear combination of $\hat{\Theta}_1$ and $\hat{\Theta}_2$

$$\hat{\Theta} = \alpha_1 \hat{\Theta}_1 + \alpha_2 \hat{\Theta}_2 . \tag{9}$$

Minimum mean squared error weights α_1 and α_2 are obtained by minimizing $E(\hat{\Theta} - \Theta)^2$. The following are the minimum mean squared error weights

$$\alpha_1^{opt} = \frac{(\Theta + B_1)\tau_2^2}{\tau_1^2(\Theta + B_2)^2 + \tau_2^2(\Theta + B_1)^2 + \tau_1^2 \tau_2^2} \Theta \tag{10}$$

$$\alpha_2^{opt} = \frac{(\Theta + B_2)\tau_1^2}{\tau_1^2(\Theta + B_2)^2 + \tau_2^2(\Theta + B_1)^2 + \tau_1^2 \tau_2^2} \Theta . \tag{11}$$

The corresponding minimum MSE is

$$MSE^{opt} = \frac{\Theta^2}{1 + (\Theta + B_1)^2 / \tau_1^2 + (\Theta + B_2)^2 / \tau_2^2} . \tag{12}$$

Unfortunately, the optimum weights to use depend on the value of Θ. Later in this section, we shall describe how the weights can be estimated in practice.

When two unbiased estimators are being combined (i.e. $B_1=0$ and $B_2=0$) and it is desired that the combined estimators also be unbiased, then the weights need to be constrained to sum to unity. In this case the optimal weight on $\hat{\Theta}_1$ can be shown to be

(13)

$$\alpha = \frac{MSE_2 - B_1 B_2}{MSE_1 + MSE_2 - 2 B_1 B_2}$$

and the optimal weight on $\hat{\Theta}_2$ is thus $1-\alpha = (MSE_1 - B_1 B_2)/(MSE_1 + MSE_2 - 2 B_1 B_2)$. The MSE of the optimal constrained estimator is

(14)

$$MSE^{opt} = \frac{MSE_1 MSE_2 - B_1^2 B_2^2}{MSE_1 + MSE_2 - 2 B_1 B_2} \ .$$

When both estimators are unbiased Equation (13) reduces to the known result for optimally combining (linearly) two independent unbiased estimates.

The preceding results will now be applied to the problem of SINR estimation. Consider two estimators of the SINR, Θ_k. For the purpose of illustration we select the smoothed, scaled and translated pilot-sample based estimator, say $\tilde{\Theta}_k^P$, and the smoothed, scaled and translated data-sample based estimator (e.g. the non-coherent estimator), say $\tilde{\Theta}_k^D$, as the two estimators to be combined. The inventors have shown that the biases and variances of these estimators are approximated as follows

$$
\begin{aligned}
& B_k^P = 0 \\
& \left(\tau_k^P\right)^2 = \frac{2(\eta_P - 2)}{N_P^2}\left[\frac{(1+N_P \Theta_k)^2}{(\eta_P - 2)(\eta_P - 4)} + \frac{1 + 2 N_P \Theta_k}{\eta_P - 4}\right] \quad (\eta_P > 4) \\
& B_k^D = \Theta_{z,k} - \Theta_k \\
& \left(\tau_k^D\right)^2 = \frac{2(\eta_D - 2)}{N_D^2}\left[\frac{(1+N_D \Theta_{z,k})^2}{(\eta_D - 2)(\eta_D - 4)} + \frac{1 + 2 N_D \Theta_{z,k}}{(\eta_D - 4)}\right] \quad (\eta_D > 4) \ .
\end{aligned}
$$

(15)

In Equation (15), the superscript and subscript P denotes the pilot sample based variables, the superscript and subscript D denotes the data sample based variables, N_D and N_P are the number of data and pilot symbols respectively per time slot, $\eta_P = (N_P - 1)(2-r)/r$, $\eta_D = (N_D - 1)(2-r)/r$ (where r is the EWMA smoothing factor) and the quantity

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$$\Theta_{Z,k} = \frac{\mu_{Z,k}^2}{\sigma_{Z,k}^2},$$

where

$$\mu_{Z,k} = \sqrt{\frac{2}{\pi}} \exp\left(-\frac{\Theta_k}{2}\right) + \frac{\sqrt{\Theta_k}}{2}\left[\text{erfc}\left(-\sqrt{\frac{\Theta_k}{2}}\right) - \text{erfc}\left(\sqrt{\frac{\Theta_k}{2}}\right)\right]$$

$$\sigma_{Z,k}^2 = \Theta_k + 1 - \mu_{Z,k}^2$$

(erfc in the above equation is the well-know complementary error function). Using Equation (15) with either Equation (10) and Equation (11) or Equation (13) gives the optimal combined estimators of $\tilde{\Theta}_k^c$ and $\tilde{\Theta}_k^D$. Since the biases and variances, and therefore the weights themselves depend on Θ_k, which is unknown, one can only

10 *estimate* the weights in practice. An estimate of the weights can be obtained by replacing Θ_k by $\tilde{\Theta}_k^c$ in the corresponding expressions. One could, alternatively, replace Θ_k by $\tilde{\Theta}_k^D$ to obtain estimates of these quantities. However, since $\tilde{\Theta}_k^c$ is an unbiased estimate of Θ_k, the accuracy of the composite estimate is better, when $\tilde{\Theta}_k^c$ is used. Note that the above technique for combining may be used with any two estimators as long as the appropriate

15 bias and variance expressions are used in the weight computation. For example, one can combine unsmoothed, scaled and translated pilot and data-sample based estimators using the same approach.

Let $C1$ denote the combined estimator of $\tilde{\Theta}_k^c$ and $\tilde{\Theta}_k^D$ that has constrained weights and $C2$ denote the combined estimator with unconstrained weights. The optimal weights

20 used when $\tilde{\Theta}_k^c$ and $\tilde{\Theta}_k^D$ are combined for $C1$ and $C2$ are shown in Figure 3, as a function of Θ_k. In the figure-legend BCSV (BCSV-Z) stands for the smoothed, scaled and translated pilot (data) sample based estimator. The root mean squared error (RMSE) values for $C1$ and $C2$ when estimated weights are used are shown in Figure 4. For comparison, the corresponding RMSE values for each of the component estimators,

25 BCSV and BCSV-Z, are also shown. (The label "A" in the figure merely means that numerical results were obtained from analytic formulas rather than simulations). Despite the error in estimating the weights, both combined estimators outperform the individual estimators for the entire range of SINR considered.

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The invention being thus described, it will be obvious that the same may be varied in many ways. Such variations are not to be regarded as a departure from the spirit and scope of the invention, and all such modifications as would be obvious to one skilled in the art are intended to be included within the scope of the following claims.

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